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Resource Allocation and User Association in User-Centric Dense mmWave Cellular Networks

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***Abstract*—User-centric overlapped clustering, relying on base station (BS) cooperation, is a promising architecture for densely deployed BSs in millimeter-wave (mmWave) networks. In this architecture, a user can be served by a set of cooperating BSs which reduces the interference received from neighboring BSs. This paper studies the problem of maximizing the number of served users in a dense mmWave network while guaranteeing the quality of service (QoS) required by each UE, defined by a received signal quality. Since the formulated problem is NP-hard, two near-optimal solutions are proposed that perform clustering and resource allocation. The first is a heuristic algorithm that builds the clusters by greedily associating the user with as many BSs as needed. The second approach is a binary particle swarm optimization (PSO) algorithm adapted to our constrained problem. Simulations confirm that the proposed algorithms approach the optimal solution with substantially lower computational complexity.**

***Index Terms*—mmWave, user-centric, user association, channel/power allocation, particle swarm optimization (PSO).**

I. Introduction

Recently, the number of cellular network users and the size of exchanged data have dramatically increased. As a result, cellular networks face several challenges, including availability, affordability, and challenging demands for high speed and low latency. However, end users always seek to benefit from excellent connectivity, even in high-density situations. Regular heterogeneous networks consisting of macrocells and several small cells sometimes cannot meet these requirements [1]. In order to remedy this, new technologies have emerged including the use of millimeter wave (mmWave) communications, which offer short range directive propagation and larger frequency bands [2]. In addition, a dense deployment of base stations (BSs) may result in significant capacity improvement [3]. However, the challenge is to mitigate the interference caused by overlapping BSs coverage. Thus, this paper investigates a user-centric approach, where each user equipment (UE) can be jointly served by a cluster of BSs.

With the densification of wireless networks, user-centric approaches are seen as promising design principles that can satisfy the high quality of service (QoS) requirements of UEs. As a result, several works studied these approaches from different perspectives. The work in [4] investigated the problem of orthogonal training resource allocation for a user-centric cooperative network. It proposed an allocation scheme for large-scale networks that minimizes the overhead costs of training, based on graph theory. The proposed scheme achieves more interesting results than systems with fixed clustering.

The problem of resource allocation in ultradense networks (UDNs) based on a user-centric architecture is studied in [5], [6], and [7]. In fact, UDNs face challenges, including limited availability of orthogonal resource blocks (RBs) and traffic load balancing. To tackle these challenges, [5] proposes to maximize the spectral efficiency by optimizing the clustering and resources allocation under RB constraints. First, a new distributed user-centric overlapped clustering is developed. Then, the orthogonal RBs are allocated to the clusters, based on graph coloring, in order to attenuate the resulting inter-cluster interference. The work in [6] maximizes the weighted sum rate under wireless backhaul constraints in UDNs, while considering the user-centric clustering in access links. In [7], a distributed scheme is proposed to approximate the joint optimization of two subproblems: user-centric overlapped clustering and resource allocation based on graph coloring. Their two-step distributed solution confirmed the superiority of the user-centric joint clustering design. Unlike this work, both [6] and [7] do not consider frequency band allocation, nor communications over mmWave frequencies.

The work in [8] studies a user-centric dense network over mmWave, where access points and blockages are randomly distributed. Stochastic geometry is used to perform an analysis of coverage probability and ergodic capacity under three different small-scale fading distributions. Performance analysis shows that BS cooperation can provide high coverage performance and noticeable capacity gain in the region where the BS density is low. The authors in [9] also use stochastic geometry to analyze the probability of coverage and the average spectral efficiency, with mmWave communications. They provide a user-centric clustering approach that selects dynamically the BSs based on the user's channel states. However, they do not consider user association; they assume a Poisson Point Process (PPP) model and focus on studying a typical user.

In this work, our goal is to maximize the number of associated users under QoS constraints. The studied problem is first formulated as a mixed integer nonlinear program and is shown to be NP-hard. Therefore, two approaches performing clustering, user association and power allocation are proposed to solve efficiently the computational complexity vs. performance trade-off. The first approach is called the greedy association and power allocation algorithm (GAPA). It proceeds in two separate phases: the first phase builds clusters by associating the user with as many BS as necessary to satisfy the SINR constraints, whereas the second phase performs an independent power allocation for each obtained association. The second approach is a particle swarm optimization (PSO) algorithm. Since the optimization variables modeling user association and frequency allocation are binary, we design a binary PSO where particles are represented by binary three-dimensional matrices. The proposed algorithm ensures the feasibility of the particle in all iterations through a repairing mechanism. Computational complexities of the two proposed algorithms are calculated and shown to be much lower than the one of the optimal algorithm.

The rest of this paper is organized as follows. The system model is presented in Section II. Section III formulates the problem. Section IV details the proposed heuristic solution. The adapted particle swarm optimization is presented in section V. The simulation results that compare the two proposed algorithms with several benchmarks are provided in Section VI and the conclusions are finally offered in Section VII.

II. System model

We consider a dense network that uses mmWave frequency bands, composed of U users and B BSs. Let $\mathcal{U} = \{1, ..., U\}$ and $\mathcal{B} = \{1, ..., B\}$ denote respectively the sets of users and BSs. We assume that each BS uses C channels where $\mathcal{C} = \{1, ..., C\}$ denotes the set of channels. A channel can be reused for serving multiple users and only one channel can be assigned to each user. We consider a user-centric architecture where each user is associated and served by one or multiple BSs that jointly transmit the same data. This joint transmission allows to guarantee a good quality of transmission and hence to satisfy the user signal-to-interference-plus-noise ratio (SINR) requirement. Having more than one channel, a BS can serve multiple users and may belong to different clusters at the same time, thus creating a user-centric and overlapped clustering architecture. An example of this architecture with 6 users, 10 BSs, and 3 channels per BS is shown in Figure 1.

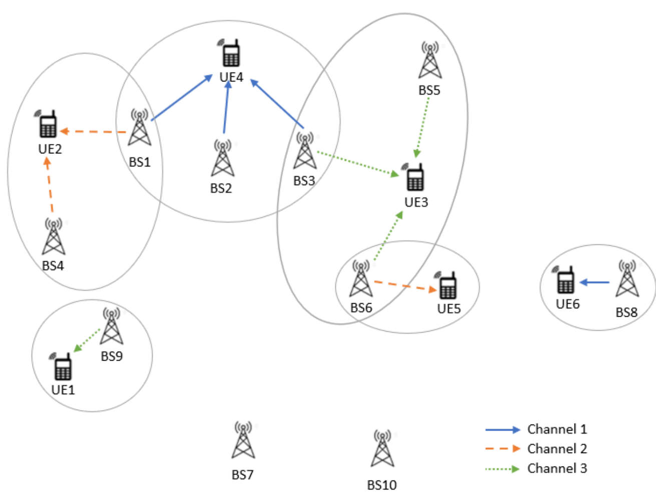

Figure 1. An example of user-centric overlapped clustering.

We notice, for instance, in Figure 1 that UE4 is served by BS1, BS2 and BS3 on channel 1 and that BS1 also serves UE2 on channel 2. That means BS1 is simultaneously a member of the two clusters serving UE4 and UE2. Since the channels can be reused, intrachannel communications will interfere with each other.

In this paper, all BSs are equipped with directional beamforming antenna arrays. The gain pattern of an antenna array is described according to the model in [10] and [9]. The antenna gain $G(\theta)$ is expressed as:

$$G(\theta) = \begin{cases} G_M, & |\theta| \leq \theta_T/2 \\ G_S, & \text{otherwise} \end{cases} \tag{1}$$

where G_M and G_S are the directional gains in the main lobe and the side lobes, respectively, θ denotes the angle of direction and θ_T is the beam width of the main lobe.

Since signals are transmitted over mmWave frequencies, they are more sensitive to blockages. We assume the line-of-sight (LOS) ball model [11], where the LOS probability function is modeled as $P_{LOS}(d) = \mathbb{1}(d < R)$ where $\mathbb{1}$ is the indicator function, d is the distance separating the transmitter and receiver, and R is the maximum length of a LOS link. Furthermore, as pointed out in [12], LOS and Non-LOS links present different results on the transmitted signals and different path loss exponents due to high penetration loss in the mmWave bands. Therefore, we consider the same path loss modeling as in [12], including different exponents α_L and α_{NL} for LOS and NLOS propagations respectively.

Note that the distribution of the small-scale fading is also different in LOS and NLOS links. The channel coefficient is assumed to follow a Nakagami-m probability distribution where m indicates the degree of fading severity. In fact, fading in mmWave LOS links is less severe and, therefore, is modeled by a relatively high fading severity [9]. Therefore, the small-scale channel gain is a Gamma random variable, that is, $h \sim \Gamma(m, \frac{1}{m})$ where $\Gamma(.)$ is the Gamma function and the Nakagami parameter m is equal to m_L or m_{NL} depending on whether the propagation is LOS or NLOS, respectively.

In the considered joint transmission scheme, a set of BSs jointly transmit the same data to the user. Hence, the signal power received at user u served on channel c, is given by [9]:

$$S_{u,c} = \sum_{b \in \mathcal{G}_u} p_{c,b} G_M h_{u,c,b} PL(d_{u,b}), \tag{2}$$

where $\mathcal{G}_u$ is the serving BS cluster of user u, $p_{c,b}$ denotes the transmit power of BS b on channel c, $PL(d_{u,b})$ and $d_{u,b}$ are the path loss and the distance between BS b and user u, respectively, $h_{u,c,b}$ is the small-scale channel gain between BS b and user u over channel c.

Let $\mathcal{I}_{u,c}$ denote the set of users served on the same channel c as user u. The interference power received by user u on its allocated channel c, can be given by:

$$I_{u,c} = \sum_{v \in \mathcal{I}_{u,c}} \sum_{n \in \mathcal{G}_v} p_{c,b} G(\theta_n) h_{u,c,n} PL(d_{u,n}), \tag{3}$$

where θ_n and $G(\theta_n)$ are, respectively, the angle and the directional gain of the interference from the nth BS. Therfore, the SINR of user u on channel c, is given by:

$$\gamma_{u,c} = \frac{S_{u,c}}{N_0 + I_{u,c}}, \tag{4}$$

where N_0 is the power of thermal noise.

III. Problem Formulation

The objective of this work is to maximize the number of associated UEs, i.e., the number of users who receive an SINR greater than or equal to a threshold. The optimization variables are the $C \times B$ matrix $\mathbf{P} = [p_{c,b}]$, the $U \times C \times B$ matrix $\mathbf{X} = [x_{u,c,b}]$, and the $U \times C$ matrix $\mathbf{Y} = [y_{u,c}]$, where the elements of $\mathbf{X}$ and $\mathbf{Y}$ are defined as:

$$x_{u,c,b} = \begin{cases} 1, & \text{user } u \text{ is served by BS } b \text{ on channel } c, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

$$y_{u,c} = \begin{cases} 1, & \text{channel } c \text{ is assigned to user } u, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Thus, the SINR received at user u on channel c is given by:

$$\gamma_{u,c} = \frac{\sum_{b\in\mathcal{B}} x_{u,c,b} p_{c,b} G_M h_{u,c,b} PL(d_{u,b})}{N_0 + \sum\limits_{\substack{f\in\mathcal{U} \\ f\neq u}} \sum\limits_{b\in\mathcal{B}} x_{f,c,b} p_{c,b} G(\theta_b) h_{u,c,b} PL(d_{u,b})} \tag{7}$$

Let γ_{Th} denote the SINR threshold and P_T the total power available at each BS. The studied problem is formulated as :

$$\underset{\mathbf{X},\,\mathbf{Y},\,\mathbf{P}}{\text{maximize}} \sum_{u\in\mathcal{U}} \sum_{c\in\mathcal{C}} y_{u,c} \tag{8a}$$

$$\text{s.t. } \gamma_{u,c} \geq y_{u,c} . \gamma_{Th}, \forall u \in \mathcal{U}, c \in \mathcal{C} \tag{8b}$$

$$\sum_{c\in\mathcal{C}} x_{u,c,b} \leq 1, \forall u \in \mathcal{U}, b \in \mathcal{B} \tag{8c}$$

$$\sum_{u\in\mathcal{U}} x_{u,c,b} \leq 1, \forall c \in \mathcal{C}, b \in \mathcal{B} \tag{8d}$$

$$y_{u,c} - x_{u,c,b} \geq 0, \forall u \in \mathcal{U}, c \in \mathcal{C}, b \in \mathcal{B} \tag{8e}$$

$$\sum_{c\in\mathcal{C}} y_{u,c} \leq 1, \forall u \in \mathcal{U} \tag{8f}$$

$$\sum_{c\in\mathcal{C}} p_{c,b} \leq P_T, \forall b \in \mathcal{B} \tag{8g}$$

$$x_{u,c,b} \in \{0,1\}, \forall u \in \mathcal{U}, c \in \mathcal{C}, b \in \mathcal{B} \tag{8h}$$

$$y_{u,c} \in \{0,1\}, \forall u \in \mathcal{U}, c \in \mathcal{C}. \tag{8i}$$

$$p_{c,b} \geq 0, \forall c \in \mathcal{C}, b \in \mathcal{B} \tag{8j}$$

Constraints (8b) ensure that the SINR required by served user is satisfied. Constraints (8c) ensure that only one channel is assigned per user. Constraints (8d) indicate that channel c in BS b is assigned to a single user. Constraints (8e) and (8f) ensure that a user is served on the same channel by all associated BSs. Constraints (8g) ensure that the sum of all the power portions allocated by a BS do not exceed its maximum power. Finally, constraints (8h), (8i) and (8j) ensure that $x_{u,c,b}$ and $y_{u,c}$ are binary variables and that the power portions take only positive values.

In the following, we discuss the NP-hardness of the formulated problem. First, it is easy to prove that it is in class NP, since given a user association and channel/power allocation solution, it can be easily verified in polynomial time. Next, consider a special case of our problem, which is a one-to-one association where each user can be served by a single BS and where all BSs are using the same channel, that is, $C = 1$. This special case of the problem is equivalent to the problem formulated in [13] which has been proven to be NP-hard. We therefore deduce that our problem (8) is also NP-hard.

IV. The Greedy Association and Power Allocation Algorithm (GAPA)

Due to the high computational complexity of the studied problem, this section proposes a heuristic algorithm that solves the problem in two phases in a greedy fashion. The main idea of this algorithm is to proceed one channel at a time while running phase 1 to obtain user association, then phase 2 to perform power allocation. Phase 1 associates the users one by one, prioritizing the BSs with the best channel gain, until the SINR is satisfied. In this phase, the transmission power allocated to the channel in each BS is assumed to be the maximum available power. Phase 2 calculates and allocates the available power based on the output of phase 1.

Algorithm 1 GAPA algorithm

Input: $\mathcal{U}, \mathcal{C}, \mathcal{B}, B, \mathbf{P} = [p_{b,c}], \mathbf{t}, \gamma_{Th}$.
Output: $\mathbf{X}$ and $\mathbf{P}$

$\mathbf{X} \leftarrow 0$, $\mathbf{Y} \leftarrow 0$.
for $c \in \mathcal{C}$ **do**
  Phase 1: User Association
  for $u \in \mathcal{U}$ **do**
    Sort $\mathbf{t}$ in descending order according to channel's gain for u on c
    $i \leftarrow 0$
    repeat
      $b \leftarrow \mathbf{t}[i]$
      if $\sum_{u\in\mathcal{U}} x_{u,c,b} < 1$ **then**
        $x_{u,c,b} \leftarrow 1$
        for $f \in \mathcal{U}$ with $f \neq u$ **do**
          if $(y_{f,c} = 1) \wedge (\gamma_{f,c} < \gamma_{Th})$ **then**
            $x_{u,c,b} \leftarrow 0$
      $i \leftarrow i + 1$
    until $(\gamma_{u,c} \geq \gamma_{Th}) \vee (i = B)$
    if $\gamma_{u,c} \geq \gamma_{Th}$ **then**
      $y_{u,c} = 1$
    else
      for $b' \in \mathcal{B}$ **do**
        $x_{u,c,b'} \leftarrow 0$
  Phase 2: Power Allocation
  for each user u associated in step 1 **do**
    for $b \in \mathcal{B}$ **do**
      Compute $p_{c,b}$
      Update $\mathbf{P}$

The proposed greedy algorithm is presented in Algorithm 1. Let $\mathbf{t}$ be a vector that contains all BSs indices. Also, each element of the power matrix $\mathbf{P}$ is initialized with P_T.

The algorithm proceeds one channel at a time and performs phases 1 and 2, successively, over exactly C iterations. Phase 1 proceeds user by user and associates the uth user with as many BSs as necessary to satisfy the requested SINR threshold γ_{Th} starting with the BS with the best channel gain. In addition, phase 1 makes sure that the current association does not disturb the previous associations by performing at most U additional iterations. The worst-case computational complexity of this phase is $\mathcal{O}(BU^2)$. Phase 2 then proceeds, for each associated user, by calculating the power required for each BS, starting with the one experiencing the highest channel gain. As the BSs are already sorted in Phase 1, there is no extra complexity incurred in Phase 2. Furthermore, once the SINR of the considered user is satisfied at a given step of the phase, there is no need to consider more BSs. The worst-case computational complexity of this phase is $\mathcal{O}(BU)$. Therefore, the overall worst-case complexity of GAPA is $\mathcal{O}(CBU^2)$.

V. Particle swarm association Algorithm

This section proposes a particle swarm optimization (PSO) algorithm to efficiently solve the studied problem with a computational complexity comparable to that of GAPA. PSO is an optimization metaheuristic based on the collaboration of a group of poorly intelligent individuals. These individuals can have a complex global organization using very simple rules of movement in the search space. At each iteration, the particles move according to their current positions, their best positions, and the best global solution.

A. Solution representation

Input: A swarm of particles L, where the position $\boldsymbol{\pi}_l$ of particle l is a three-dimensional $U \times C \times B$ binary matrix, whose elements are given by:

$$\pi_l(u,c,b) = \begin{cases} 1, & \text{user } u \text{ is served on channel } c \text{ by } b, \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

Fitness function: To measure the quality of the association, $f_t(\boldsymbol{\pi}_l)$ evaluates the number of associated users of particle i.

Output: $gbest$ that is a $U \times C \times B$ binary matrix corresponding to the particle that maximizes the fitness function.

Stopping criteria: The algorithm terminates when a maximum number of iterations is performed or all users are associated.

Particle velocity: Each particle l in iteration k moves with velocity v_l^k in the search space. This velocity is given by a three-dimensional matrix of size $U \times C \times B$, where each element of the matrix is restricted to $[v_{min}, v_{max}]$. After each move, the velocity is updated as follows:

$$\begin{aligned} v_l^{k+1}(u,c,b) &= \omega^k v_l^k(u,c,b) \\ &+ w_1 r_1 \times (pbest_l^k(u,c,b) - \pi_l^k(u,c,b)) \\ &+ w_2 r_2 \times (gbest^k(u,c,b) - \pi_l^k(u,c,b)) \end{aligned} \quad (10)$$

where $pbest_l^k(u,c,b)$ is the particle best recorded position until iteration k, $gbest^k(u,c,b)$ is the global best, r_1 and r_2 are uniform random numbers in $[0,1]$, w_1 and w_2 are weighting coefficients for the personal best and global best (also known as social and cognitive parameters) and finally, ω^k is an inertia factor where $\omega^k = \frac{1+\beta}{\beta+k}$, with β a randomly chosen value.

We use the piece-wise linear function to force velocity values to be inside the allowable interval of values,

$$h(v_l^{k+1}(u,c,b)) = \begin{cases} v_{max}, \text{ if } v_l^{k+1}(u,c,b) > v_{max} \\ v_{min}, \text{ if } v_l^{k+1}(u,c,b) < v_{min} \\ v_l^{k+1}(u,c,b), \text{ otherwise.} \end{cases} \quad (11)$$

Since the particles are binary valued, we use the sigmoid function [14] that is given by $sig(y) = \frac{1}{1+e^{-y}}$ to force the real values obtained after moving a given particle to fall between 0 and 1. Then each element $\pi_l^{k+1}(u,c,b)$ is set to 1 if and only if

$$sig(h(v_l^{k+1}(u,c,b))) < random[0,1] \quad (12)$$

Conditions: The particle positions are updated according to the calculated velocity only if (8d)–(8g) are respected. Otherwise, all particle elements are forced to be equal to zero.

Note that the SINR constraints and power allocation are not taken into account when updating the particle positions, and hence the obtained associations may not respect the constraints (8b). Thus, a repair function [15] is used to test the SINR condition and allocate the necessary power using GAPA phase 2. In this case, the function repairs the particle to find a feasible solution by setting the particle elements to zero.

Algorithm 2 PSO algorithm

Input: a swarm of L particles
Output: $gbest$ = the best particle

1: Initialize the particles positions
2: Initialize the particles velocities randomly
3: Initialize $pbest_l^0$ for all particles with

$$pbest_l^0(u,c,b) = \pi_l^0(u,c,b)$$

4: Evaluate each particle with $f_t(\pi_l^0)$
5: Initialize $gbest^0$ for all particles with

$$f_t(gbest^0(u,c,b)) = \max_i\{f_t(pbest_l^0(u,c,b))\}$$

6: Set iteration number $k \leftarrow 1$
7: **while** (*Stopping criteria is not reached*) **do**
8: Update velocity according to (10)
9: Update particles positions according to (11) and (12)
10: Ensure that constraints (8c)–(8g) are respected
11: Repair the positions if necessary
12: Measure fitness
13: Update $pbest$ and $gbest$
14: $k \leftarrow k+1$

B. Initialization

Three approaches are tested in this work:

- *RandomInit*: the algorithm generates L random particles, according to the discrete uniform distribution, respecting constraints (8c)–(8g).
- *HeuristicInit*: the algorithm generates $L-1$ random particles, according to the discrete uniform distribution, respecting constraints (8c)–(8g) and add a Lth particle corresponding to the GAPA solution.
- *HeuristicModInit*: It is similar to *HeuristicInit*, but replaces a given number of particles with a close to GAPA solutions, i.e. setting random elements to 1.

C. Computational complexity

The adapted PSO algorithm is presented in Algorithm 2. In the initialization phase, the algorithm generates L particles and L velocities in $\mathcal{O}(UCBL)$ steps. Next, for each iteration, it updates the particle positions in $\mathcal{O}(UCB)$, verifies the conditions in $\mathcal{O}(UC^2B^2)$ steps and calls the repair function whose complexity f_{repair} depends on the employed strategy. The total computational complexity for the PSO algorithm is thus equal to $\mathcal{O}((UC^2B^2 + \mathcal{O}(f_{repair}))KL)$.

VI. SIMULATION RESULTS

This section presents several simulation results illustrating the performance of the two proposed algorithms, GAPA and PSO. They are compared to three benchmarks namely the optimal solution (OPT), the one-to-one association (1to1-A) and the random algorithm (RA). The optimal performance is obtained using the APOPT (Advanced Process OPTimizer) solver of GEKKO package under Python. The 1to1-A algorithm, with computational complexity of $\mathcal{O}(CBU^2)$, does not consider overlapping clustering and assumes that a user may be associated with at most one BS. Also, the RA selects a random user at each iteration and tries the association. The computational complexity of the RA is $\mathcal{O}(CBU)$.

We consider that U UEs are uniformly distributed in a squared area of size A. The BSs are distributed considering that the simulation area is organized in hexagons and each BS is placed in the center of a hexagon. By default, $C = 4$ unless otherwise specified. The PSO algorithm is initialized according to *HeuristicInit* approach since it is found through simulations that it converges faster than *RandomInit* and *HeuristicModInit*. The remaining simulation parameters are shown in Table I.

Table I
SIMULATION PARAMETERS.

Notations	Description	Value
A	Simulation area	100m $\times$100m
γ_{Th}	SINR threshold	10 dB
P_T	BS transmit power	30dBm [9]
W	Channel bandwidth	200MHz
	Noise power spectral density	-174dBm/Hz
R	Maximum LOS link length	10m
(m_L, m_{NL})	LOS and NLOS Nakagami parameter	(3, 2) [9]
(α_L, α_{NL})	LOS and NLOS path loss exponent	(2.2,4) [9]
(G_M, G_S)	BS antenna arrays parameters	(20 dB,0 dB)
θ_T	Beam width	45°
L	Number of particles in the swarm	$2U$
K	Number of iterations (PSO)	$U \times C \times B$
v_{max}, v_{min}	Maximum, minimum velocity (PSO)	$4, -4$

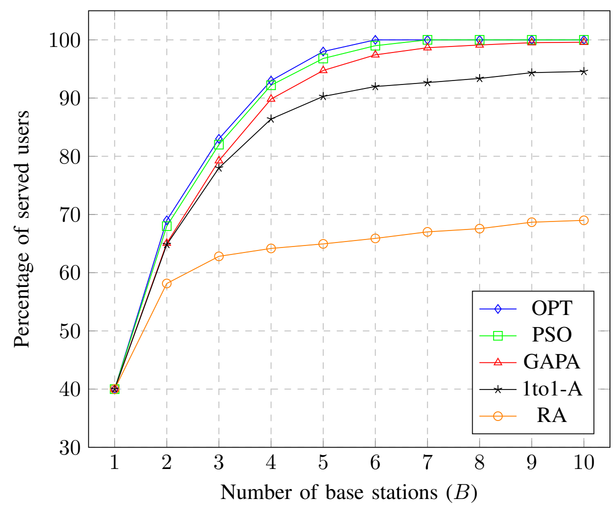

Figure 2. Percentage of associated users for $U = 10$.

Figure 2 shows the percentage of associated UEs versus the number of BSs with $U = 10$. We notice that the performance of PSO and GAPA are very close to the optimal solution with a slight advantage to the former algorithm. This is expected since GAPA has a smaller complexity and is used as an initilization particle for the PSO.

The high computational complexity of OPT prevents us from considering a value of U greater than 10. Therefore, in order to illustrate the performance of the proposed algorithms for a larger value of U, Figure 3 shows the percentage of associated UEs versus the number of BSs with $U = 20$, $\gamma_{th} = 13$dB, and $C = 3$ or $C = 5$. We observe that both proposed algorithms significantly outperform 1to1-A and RA (based on Figure 2). Hence, a well designed clustering algorithm guarantees good performance with a limited increase in computational complexity.

Figure 4 shows the number of associated UEs while varying the total number of UEs with $B = 4$. Here again, we observe that GAPA performs very well even when increasing the number of UEs U, with a worst case performance gap of 3.3% compared to OPT. On the other hand, PSO performance are very close-to-optimal and clearly improves GAPA solution as U gets larger. As in Figures 2 and 3, the two proposed algorithms significantly outperform the two other benchmarks.

Figure 5 shows the percentage of associated UEs while varying the SINR threshold. We set the other parameters as $U = 10$, $B = 4$ and $C = 3$ or 5. As the SINR threshold gets higher, the number of associated users decreases because of the system limited resources. However, even for high SINR threshold values, the performance of GAPA and PSO remains close to optimal and both take advantage of adequate BS clustering and adapted power allocation. They thus clearly outperform 1to1-A solutions.

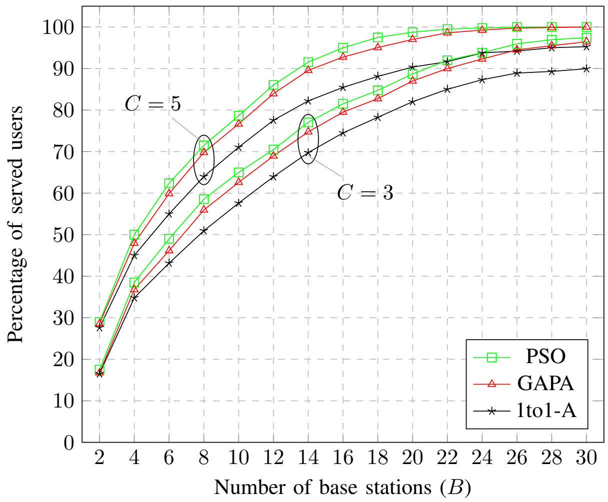

Figure 3. Percentage of associated UEs for $U = 20$.

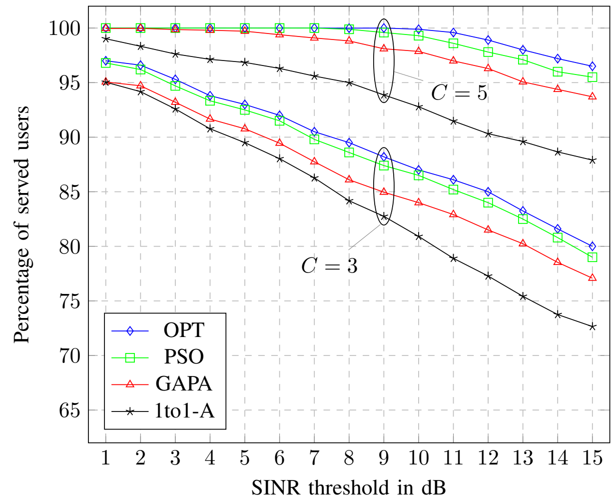

Figure 5. Impact of the SINR threshold for $U = 10$ and $B = 4$.

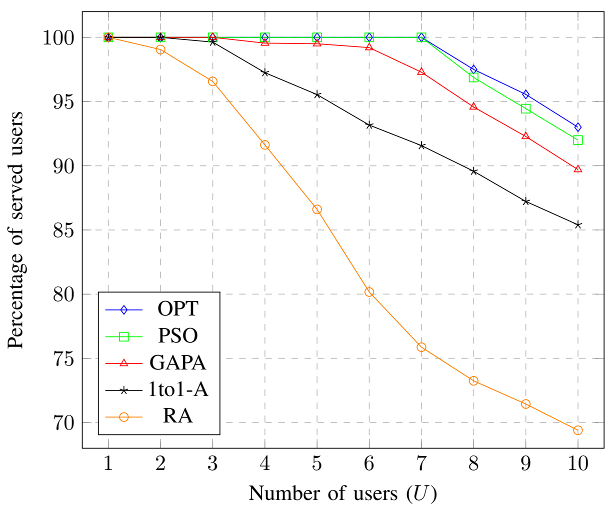

Figure 4. Impact of the total number of users for $B = 4$.

VII. Conclusion

In this paper, we investigated the user-base station association and the channel/power allocation problem considering user-centric dense network that employs mmWave communications. The formulated integer non-linear problem is to maximize the number of associated users under the constraint of guaranteeing quality of service, defined by SINR threshold, for each user. Since this problem is shown to be NP-hard, two low-complexity algorithms were proposed, namely the greedy association and power allocation algorithm and the particle swarm optimization algorithm. Numerical results showed that our proposed algorithms solve differently the performance/-complexity tradeoff but they both achieve close to optimal performance with a highly reduced computational complexity.

References

[1] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. K. Soong, and J. C. Zhang, "What Will 5G Be?" *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1065–1082, 2014.

[2] S. Rangan, T. S. Rappaport, and E. Erkip, "Millimeter-Wave Cellular Wireless Networks: Potentials and Challenges," *Proc. IEEE*, vol. 102, no. 3, pp. 366–385, 2014.

[3] M. Kamel, W. Hamouda, and A. Youssef, "Ultra-Dense Networks: A Survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2522–2545, 2016.

[4] Z. Chen, X. Hou, and C. Yang, "Training Resource Allocation for User-Centric Base Station Cooperation Networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 4, pp. 2729–2735, 2016.

[5] Y. Lin, R. Zhang, C. Li, L. Yang, and L. Hanzo, "Graph-Based Joint User-Centric Overlapped Clustering and Resource Allocation in Ultradense Networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 5, pp. 4440–4453, 2018.

[6] Y. Luo and C. Hua, "Resource Allocation and User-Centric Clustering in Ultra-Dense Networks with Wireless Backhaul," in *Proc. Int. Conf. on Wireless Commun. Signal Processing (WCSP)*, 2016, pp. 1–5.

[7] L. Liu, V. Garcia, L. Tian, Z. Pan, and J. Shi, "Joint Clustering and Inter-Cell Resource Allocation for CoMP in Ultra Dense Cellular Networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2015, pp. 2560–2564.

[8] J. Shi, C. Pan, W. Zhang, and M. Chen, "Performance Analysis for User-Centric Dense Networks With mmWave," *IEEE Access*, vol. 7, pp. 14 537–14 548, 2019.

[9] K. Humadi, I. Trigui, W.-P. Zhu, and W. Ajib, "Dynamic Base Station Clustering in User-Centric mmWave Networks: Performance Analysis and Optimization," *IEEE Trans. Commun.*, vol. 69, no. 7, pp. 4847–4861, 2021.

[10] H.-M. Wang, K.-W. Huang, and T. A. Tsiftsis, "Base Station Cooperation in Millimeter Wave Cellular Networks: Performance Enhancement of Cell-Edge Users," *IEEE Trans. Commun.*, vol. 66, no. 11, pp. 5124–5139, 2018.

[11] J. G. Andrews, T. Bai, M. N. Kulkarni, A. Alkhateeb, A. K. Gupta, and R. W. Heath, "Modeling and Analyzing Millimeter Wave Cellular Systems," *IEEE Trans. Commun.*, vol. 65, no. 1, pp. 403–430, 2017.

[12] T. S. Rappaport, G. R. MacCartney, M. K. Samimi, and S. Sun, "Wideband Millimeter-Wave Propagation Measurements and Channel Models for Future Wireless Communication System Design," *IEEE Trans. Commun.*, vol. 63, no. 9, pp. 3029–3056, 2015.

[13] Z. Mlika, M. Goonewardena, W. Ajib, and H. Elbiaze, "User–Base-Station Association in HetSNets: Complexity and Efficient Algorithms," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1484–1495, 2017.

[14] M. Tasgetiren and Y.-C. Liang, "A Binary Particle Swarm Optimization Algorithm for Lot Sizing Problem," *Journal of Economic and Social Research*, vol. 5, 01 2004.

[15] W. S. Atoui, W. Ajib, and M. Boukadoum, "Offline and Online Scheduling Algorithms for Energy Harvesting RSUs in VANETs," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 6370–6382, 2018.